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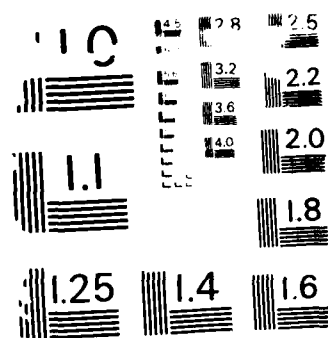
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DEPT OF ELECTRICAL AND COMPUTER ENGI... W T CATHEY
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| 19. ABSTRACT (Continue on reverse if necessary and identify by block number) To investigate uses of optics in artificial intelligence (AI), 25 researchers met for 2-1/2 days at Gold Lake, CO, from 3-5 August 1987. The purpose was to bring together optics and AI researchers to define the problems and opportunities for the optical solution of AI problems. The group broke into three subgroups that considered (1) perception, (2) optical data base/knowledge base machines, and (3) learning. The entire workshop group first met to select the areas for discussion and the means of conducting the workshop. Three areas were chosen, each with a working group. During the period of the workshop, meetings alternated between the three subgroups and the entire group which facilitated communication between groups. | | | | | |
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WORKSHOP ON OPTICAL ARTIFICIAL INTELLIGENCE

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To investigate uses of optics in artificial intelligence (AI), 25 researchers met for 2-1/2 days at Gold Lake, Colorado, from 3-5 August 1987. The purpose was to bring together optics and AI researchers to define the problems and opportunities for the optical solution of AI problems. The group broke into three subgroups that considered (1) perception, (2) optical data base/knowledge base machines, and (3) learning.

The workshop was funded by the Air Force Office of Scientific Research and the Office of Naval Research. It was jointly sponsored by the Center for Optoelectronic Computing Systems and was organized by W. Thomas Cathey, Center for Optoelectronic Computing Systems, University of Colorado; H. John Caulfield, Center for Applied Optics, University of Alabama; Sing Lee, University of California, San Diego; and Harold Szu, Naval Research Laboratories. The local organization was handled by the Center for Optoelectronic Computing Systems.

The entire workshop group first met to select the areas for discussion and the means of conducting the workshop. Three areas were chosen, each with a working group. During the period of the workshop, meetings alternated between the three subgroups and the entire group which facilitated communication between groups.

Reports from the subgroups on learning, optical data base/knowledge base machines, and perception follow.



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Learning Group

The group discussing learning was made up of Yaser Abu-Mostafa, Dana Anderson, Marcus Cohen (part time), Shelly Dalton, Art Fisher, Lee Giles (part time), Kristina Johnson, Alastair McAulay, John Neff, Herschel Pillof, and Carl Verber,

An attempt was made to define the learning problem domain by considering a broad sample of the potential applications of learning. A wide collection of paradigms with diverse capabilities and application domains was elucidated. Problems were found with many current approaches toward learning, and performance measures were discussed which point to wide lists of desirable features for learning systems. Consideration turned toward the potential impacts of optics in overcoming difficulties and enhancing the learning endeavor. Finally, three critical problem areas were isolated for enhancing the capabilities of learning in optical artificial intelligence. These are:

- 1) Development of a library of test cases for evaluating the performance of a diverse variety of learning systems.
- 2) Building a general multi-layer optical connection system with off-line learning initially and
- 3) Optical implementation of a learning system with a high level of performance capability without incurring a high penalty in implementational complexity.

Optics offers a unique three-dimensional interconnect capability for moving 2-D data fields in, out, and between learning systems. Furthermore, the parallel computational abilities of optics can be exploited to implement the parallel computation intrinsic to most learning formulation (e.g., connectionist and associative approaches). Optics offers high-density memory capabilities for storing intermediate and final learned information. Analog optics can facilitate incremental learning. A digital implementation can require extensive computational hardware and many bits of precision to accumulate a small measurement to a large learned quantity. An optical system, however, can take an increment of small quantities - limited levels and integrate it into a much larger low-precision signal. Optics can also perform analog N-array addition, where all N numbers in a simulation are simultaneously added as intensities on a detector. Furthermore, optics allows information to be represented as continuous spatial distributions, subject to resolution limitations, rather than as discrete matrices or vectors. Continuous representations generally increases information capacity in terms of numbers of patterns which can be reliably stored.

Optics intrinsically offers additional operations which are fundamental to many learning formulations, such as overlap integrals, convolution, and correlation. The physics of optical materials brings additional capabilities such as nonlinearities and other more advanced operations. Finally, and perhaps most intriguingly, optical systems offer completely novel learning mechanisms in some cases, and are leading to the discovery of new learning formulations.

In the opinion of the group, there are three tasks which should be carried out to further the development of optical AI. In order of immediacy these are: Development of a library of standard AI test cases for the evaluation of AI algorithms and of simulated optical AI machines; construction of a simple hybrid optical/electronic neural net to evaluate optical components, to develop an appreciation for the modalities of optical

system design and possibly to produce a machine useful in applications requiring only infrequent learning; development of optical computational primitives and methods for using them to implement all-optical learning.

It was felt that a library of at least six test cases should be derived which serve to elucidate various aspects of machine performance and will allow comparison of different machines. It is essential that all details of the systems used be well documented. A minimal list of parameters for neural architectures includes

| | |
|-------------------|-------------------------|
| Type of system | Update rules |
| Running Time | Feedback ? |
| Neural net size | Number of interconnects |
| Weights | Number of layers |
| Analog or digital | |
| Number | |
| Dynamic range | |

It is essential that the test be as bias-free as possible. An example is a pattern-recognition test in which a library of 2000 training samples is provided, half of which contain the same randomly generated "object" buried in random noise (the "1" data) and half of which contain only noise (the "0" data). After training with this set, the systems are evaluated using the criteria

- (i) learning time; number of passes through the training set; number of primitive computations (e.g., per node x number of nodes y number of iterations)
- (ii) % error when presented with old sample
- (iii) % error when presented with new sample
- (iv) classification time.

A second test would be a statistical problem -- the performance of a particular machine would be based upon a least-squares criterion. The sample data would consist of input/output pairs of a mapping that is to be learned. The statistics of the mapping govern the difficulty of the task. For example, the statistics of an "easy" mapping would consist of simple spherical clusters -- a sphere in the input space maps to a sphere in the output space. A more difficult mapping would be irregular but still connected subspaces (an irregular subspace of the input maps to an irregular subspace of the output). A still more difficult mapping would involve disconnected regions of an input space that map onto a single connected region of the output space. A given machine would be given a series of training sets, each successively more difficult than the previous one. The machine's performance is compared to an unambiguous Bayesian probability measure in each case.

Other tests have to be designed and should include at least one containing "real" data. (Possibilities include: imagery, speech, sonar, hand-written characters.)

Another task which should be started as soon as possible is the construction of a simple neural net. It should have the following characteristics.

- 1. minimum of 3 layers - must be expandable.

2. 32 neurons/layer - expandable to 1000
 3. global interconnect between layers with complete fan out capability
 4. perform with linear weights (optically)
 5. perform with threshold (preferably optically)
 6. learning - can be electronic in first machines. (Note: There are potential applications (ex., text to speech) where all the learning can be handled offline and then downloaded into a fixed-weight machine.) An optical machine such as this might be very efficient, fast, and easy to manufacture in quantity. Electronically implemented learning algorithms will probably be used on the first machines. These hybrids may even find application in situations where only infrequent learning updates are required. However, in the long term, high-speed learning rules must be optically implemented. Toward this end, optical computational primitives should be developed and cataloged with the goal of devising learning algorithms which might be carried out in all- or highly-optical hardware. The following technologies were suggested as possibly providing useful computational properties.
- Incremental learning via photorefractive holograms
 - Photorefractive writing of optical connections
 - Multilayer integrated optical systems
 - Threshold on intensity - carry information on phase/polarization
 - Use Fredkin gates for decision making without photon loss
 - Phase conjugation for gain and decision making
 - Differentiation via photorefractive holograms
 - Store weights as discrete elements of analog and digital spatial light modulators.

Data Base/Knowledge Base Machines

The data base/knowledge base group consisted of Bruce Berra, Ravindra Athale, Karl-Heinz Brenner, Thomas Cathey, John Caulfield, George Eichmann, Sing Lee, Rodney Schmidt, and Harold Szu.

Of all the aspects of AI, one has spawned billions of dollars of annual commercial sales and finds itself simultaneously choking on the amount and rate of information it can now handle and desiring to handle much more. At the 1987 Gold Lake Conference, these opportunities were recognized and addressed specifically by the subgroup which devoted its efforts to the field of optics for data base and knowledge base machines.

This report summarizes the conclusions of this subgroup, but it cannot do adequately the two most important tasks identified by the group: identify the detailed opportunities for optics to revolutionize DB/KB machines and bring these opportunities to the attention of the larger optics community. To accomplish those tasks, the group will submit a detailed technical paper to Applied Optics in February of 1988. This should lead to a publication in the summer of 1988. In addition, a number of specific technological supporting concepts were developed at this conference and will be published in various journals over the next year.

The field of DB/KB machines is very broad and very dynamic. Much of the field serves its needs well and has no need of help from optics. The niche for optics arises when the DB/KB becomes huge (gigabytes to terabytes) and the situation requires "real time" (a second and sometimes much less) response. For this niche, the DB/KB community has responded with vast interconnected arrays of smart disk memory systems interconnected extensively by smart buses and using powerful computer overseers. This expensive approach is still inadequate for the need; here is the niche for optics.

A peculiar property of the giant DB/KB machines is that they already use optics (storage, fiber optics, etc.) and that there is no task involved that, in principle, cannot be done optically. This leads to the opportunity and even probability of a bottoms up change in the field so long as optics provides "transparent" modules which outperform their electronic counterparts. The step-by-step modification of this currently electronics-dominated field is what the group came to call "the electronic paradigm."

A totally different approach was also developed. This approach, "the optics paradigm," starts with the problem understanding, and an understanding of what optics can do best to solve it. The optics paradigm leads to designs more promising in meeting the needs but less promising for gradual changes in the machines. Briefly, the optics paradigm is as follows:

- Store data in highly encoded (for reliability) pages on rapidly addressable holograms,
- Respond to queries by intelligent (possibly optical neural network controlled) output of plausible pages in parallel onto smart, optically-addressed SLMs,
- Keeping these pages in parallel optical format, eliminate as many as possible from further consideration,
- Still staying in the parallel optical domain, look within the pages to flag, arrange, and concentrate the useful data, and

- Turn the results into a form needed by the user (human, electronic AI, optical AI, etc.).

Specific approaches to each of these tasks were developed and will be reported in the Applied Optics paper.

Working Group on Perception

The participants in this group were: Robert Marks (Chairman), Markus Cohen, Lee Giles, Ivan Kadar, David Morley, Rodney Schmidt, Louis Scharf.

This working group attacked the problem of perception in artificial intelligence. For the purposes of this working group, the term "perception" was defined to be "reduction of a dense array of data to a sparse meaningful description." The sense of this definition was that the final result of perception was a reduction in the size of the data set into a smaller one suitable for the larger problem in which perception was taking place. This reduction could be to a set of symbols or to a sparser array. Some group members preferred to view it as projection onto an appropriate sub-space. One of the group members presented a total system for ship detection and classification. The part of this system pertaining to perception was examined in detail.

The group sought to identify a reasonably sized problem in perception that would be particularly well suited to solution via optical means. Areas considered included intelligent preprocessing and filtering in which the size of the data set was not reduced but the data was better conditioned for subsequent processing. The next stage in perception, feature extraction, was examined with attention to the role that feedback from detection and identification could play. Segmentation of the data set into objects or "figure/background" relations was seen to be a large and unsolved problem in artificial intelligence and it was concluded that further fundamental work in basic AI research would be required before this problem would be ready for attack by optical processing.

Both 2 and 1 dimensional data were considered but discussion finally centered on two dimensional data.

Optical contributions to perception fell roughly into two categories: direct optical processing of images and ultra high speed computation of a more general nature used at all stages of the perception problem. On the latter issue, the need for a commercially attractive general purpose optically based DSP module was noted. An optical matrix-vector multiplier was proposed as a likely candidate.

Specific problems the group discussed included: (a) Robot cognition in a simple "blocks" world, (b) Optical computation of visual flow, (c) Optical computation of Dempster-Shafer evidence combinations and (d) Use of optical processors for an intelligent memory search engine. During the evening Plenary Session, a number of possible solutions to the visual flow problem were proposed. These included using coherent illumination and doppler shift detection of velocity as well as correlating an image with another made shortly later. The later image would have a line removed and result in an image of the line displaced in proportion to the movement of the line deleted from the original image.

The group discussed in detail the contribution that the Dempster-Shafer evidential reasoning technique could contribute to processing possibly incomplete and/or conflicting data.

A "Perceptual Reasoning Machine" (PRM) based problem solving paradigm was proposed by Ivan Kadar. The PRM assumes that there exists a priori knowledge about the data domain (observations) to be "perceived", i.e., to be reasoned with and interpreted.

After preprocessing the current sensory information to the "proper level of abstraction" in a feature parameter vector space (depending on the problem/application) the data are collected and processed in a "gather/assess" module whose evidence functions and algorithms generate beliefs and hypotheses about the observations in a Non-Bayesian framework, using Dempster/Shafter (D/S) theory. This is an important attribute of the PRM, since the D/S theory allows the representation of total ignorance (not knowing anything about the current information) as opposed to assuming equally likely prior distributions in a Bayesian model.

The output of the "gather/assess" module is split between evidence interpretation and feedback to an "anticipate/predict" module, which contains learning algorithms and knowledge bases, in the form of associative memory, derived from the a priori domain knowledge and from learning updates from the "gather/assess" module based on the current sensory information.

Part of the input data (current information), after preprocessing, is also used to recall prior knowledge from the "anticipate/predict" module. The associative memory construction of the "anticipate/predict" module facilitates recall of the stored data, in the least squares sense, even if only partial and/or noisy "key" data are present in the current information. The output of the "anticipate/predict" module in turn "drives", with the recalled information, the "gather/assess" module closing the feedback loop.

In the "gather/assess" module, the recalled data are combined (using D/S theory of evidence combination and propagation) with the current information. The recalled data provides support (in a negative or positive reinforcement sense) to the observed combined current data. The output of the "gather/assess" module provides domain hypotheses (likelihoods in the form of evidential intervals) for interpretation of what is being "perceived". The process can be iteratively repeated if temporal observations are available.

In an optical rendition of the PRM (both optical associative memory and optical D/S processing), the processing structure of the PRM can be thought of as providing an optically computed figure of merit for a single given memory array access directing the next memory access. The process is iteratively repeated until convergence of hypotheses are achieved.

The latter topic was the one most developed by the group. Here a model of an object to be perceived is stored in a volume hologram (later changed to a hemispherical holographic plate). Two-dimensional projections of the 3-D model would be read out of the hologram using an adaptive, optical scanning system producing a matched filter for the input data. In some versions of this approach, frequency sweeping of the read out beam was used to search scale changes in the 2-D projection of the model. Parts of the foregoing approach were suggested in a conversation of one of the group members with R. Aaron Falk of Boeing Aerospace.

The question of discovering optimal representations (feature sets) for perceived images was discussed; it was pointed out that this is also an old unsolved problem. It was then suggested that the representation be rotated "on the fly" until an optimal one for a given problem is found. Optimality would perhaps be measured by feedback from an output performance measure back to the "representation rotating engine" - when performance is optimized, the right representation must be present.

Conclusions

Twenty-five researchers met for 2-1/2 days to investigate the uses of optics in artificial intelligence. The more promising applications in three areas were identified and suggestions were made for pursuing these applications. In the field of perception, the optical computation of visual flow was felt to be an area of promise and several suggestions were made. The area of data/base knowledge base machine stimulated this subgroup to put their ideas in a joint paper that will describe the use of optics in storage, access, and processing of data in large data bases. The learning subgroup looked at the optical implementation of a learning system and concluded that a system should be built using a multi-layer optical connection system. In addition, they concluded that a library of test cases should be developed for evaluating learning systems of any type.

Recommendations

The format and venue of the conference proved conducive to serious discussion and advancement of the field. The impact was such as to warrant consideration of institutionalizing such a conference.

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